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Advancing body composition analysis: Transitioning beyond conventional BMI standards

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Abstract

Background: Body mass index (BMI) remains the primary tool for obesity classification despite its limitations in assessing body composition. This study aimed to evaluate the relationship between different body composition parameters and compare World Health Organization (WHO) and National Health and Nutrition Examination Survey (NHANES) classification systems.

Methods: In this cross-sectional study of 3,255 patients (74.3% women) from a Colombian obesity and metabolism center, we analyzed body composition using bioelectrical impedance analysis. We assessed the concordance between the World Health Organization and the National Health and Nutrition Examination Survey classifications, and examined correlations between body composition parameters, with particular focus on phase angle (PhA) as a predictor of muscle mass.

Results: While body mass index showed a strong correlation with body fat mass ($\rho = 0.929$, $p < 0.001$), it poorly predicted muscle mass. The World Health Organization and the National Health and Nutrition Examination Survey classifications showed fair overall agreement ($\kappa = 0.39$), with better concordance in women ($\kappa = 0.43$) than men ($\kappa = 0.28$). Multiple regression analyses revealed PhA as a strong predictor of muscle mass ($\beta = 1.032$, $p < 0.0001$, $R^2 = 0.332$) but not fat mass ($p = 0.525$, $R^2 = 0.055$).

Conclusions: While body mass index adequately predicts adiposity, it falls short in assessing muscle mass. Phase angle emerges as a promising predictor of muscle mass, independent of age and sex, suggesting its potential utility in clinical assessment of body composition.

Keywords: Body composition, Phase angle, Body mass index, Obesity classification, Bioelectrical impedance, Muscle mass, Fat mass, Anthropometry.

Highlights

- **Challenging BMI standards:** This study questions the utility of body mass index (BMI), highlighting its limitations in distinguishing between fat mass and muscle mass.
- **Phase angle as a predictor:** Phase angle (PhA) is introduced as a significant predictor of muscle mass, independent of age and sex, underscoring its utility in clinical assessments.
- **Comparative analysis:** The concordance and discrepancies between the World Health Organization and the National Health and Nutrition Examination Survey obesity classification systems are critically evaluated, revealing variances in their ability to classify obesity accurately.
- **Implications for clinical practice:** The findings suggest the need for incorporating more detailed body composition parameters in clinical practice to better understand obesity-related risks.

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Avanzando en el análisis de la composición corporal: trascendiendo los estándares convencionales del índice de masa corporal (IMC)

Resumen

Antecedentes: el índice de masa corporal (IMC) sigue siendo la herramienta principal para la clasificación de la obesidad a pesar de sus limitaciones para evaluar la composición corporal. Este estudio tuvo como objetivo evaluar la relación entre diferentes parámetros de composición corporal y comparar los sistemas de clasificación de la Organización Mundial de la Salud (OMS) y la Encuesta Nacional de Examen de Salud y Nutrición (NHANES).

Métodos: en este estudio transversal de 3,255 pacientes (74.3 % mujeres) de un centro de obesidad y metabolismo en Colombia, analizamos la composición corporal utilizando análisis de impedancia bioeléctrica. Evaluamos la concordancia entre las clasificaciones de la Organización Mundial de la Salud (OMS) y la Encuesta Nacional de Examen de Salud y Nutrición (NHANES), y examinamos las correlaciones entre los parámetros de composición corporal, con un enfoque particular en el ángulo de fase (PhA) como predictor de la masa muscular.

Resultados: mientras que el índice de masa corporal mostró una fuerte correlación con la masa grasa corporal ($\rho = 0.929$, $p < 0.001$), predijo pobremente la masa muscular. Las clasificaciones de la Organización Mundial de la Salud (OMS) y la Encuesta Nacional de Examen de Salud y Nutrición (NHANES) mostraron una concordancia general justa ($\kappa = 0.39$), con mejor concordancia en mujeres ($\kappa = 0.43$) que en hombres ($\kappa = 0.28$). Los análisis de regresión múltiple revelaron el PhA como un fuerte predictor de la masa muscular ($\beta = 1.032$, $p < 0.0001$, $R^2 = 0.332$), pero no de la masa grasa ($p = 0.525$, $R^2 = 0.055$).

Conclusiones: aunque el índice de masa corporal predice adecuadamente la adiposidad, no es eficaz en la evaluación de la masa muscular. El ángulo de fase emerge como un predictor prometedor de la masa muscular, independiente de la edad y el sexo, sugiriendo su utilidad potencial en la evaluación clínica de la composición corporal.

Palabras clave: composición corporal, ángulo de fase, índice de masa corporal, clasificación de la obesidad, impedancia bioeléctrica, masa muscular, masa grasa, antropometría.

Destacados:

- **Desafiando los estándares del IMC:** este estudio cuestiona la utilización del índice de masa corporal (IMC), destacando sus limitaciones para distinguir entre la masa grasa y la masa muscular.
- **Ángulo de fase como predictor:** el ángulo de fase (PhA) se introduce como un predictor significativo de la masa muscular, independiente de la edad y el sexo, subrayando su utilidad en las evaluaciones clínicas.
- **Análisis comparativo:** se evalúa críticamente la concordancia y las discrepancias entre los sistemas de clasificación de la obesidad de la Organización Mundial de la Salud (OMS) y la Encuesta Nacional de Examen de Salud y Nutrición (NHANES), revelando variaciones en su capacidad para clasificar correctamente la obesidad.
- **Implicaciones para la práctica clínica:** los hallazgos sugieren la necesidad de incorporar parámetros más detallados de composición corporal en la práctica clínica para entender mejor los riesgos relacionados con la obesidad.

Introduction

Obesity has become a major global health concern, traditionally assessed and classified using the body mass index (BMI) (1,2). While BMI provides a quick measure of excess weight, it does not account for the relative proportions of fat and muscle mass, nor does it capture fat distribution (3). As a result, individuals with the same BMI may have vastly different body composition profiles, leading to potential misclassification of their metabolic and cardiovascular risk (3-5). Considering these limitations, the focus on body composition assessment has grown, placing emphasis on more detailed measurements. Among the available tools, bioelectrical impedance analysis (BIA) has emerged as a practical, non-invasive, and cost-effective method to evaluate fat mass, muscle mass, and distribution patterns, offering a more nuanced perspective on overall health (6,7).

Beyond distinguishing between various tissue components, body composition metrics such as phase angle (PhA) have gained attention for their ability to shed light on cellular health and integrity (7,8). PhA, derived from the reactance and resistance measurements in BIA, reflects the overall function and viability of cell membranes. Higher PhA values often correlate with healthier cell membranes and better nutritional status, whereas lower values can indicate compromised cell integrity and heightened morbidity risk (8-10). By providing an additional layer of information about the body's physiological state, PhA complements traditional body composition parameters, expanding the insights available for clinicians and researchers in understanding obesity-related risks (11,12).

Given the growing necessity for a more comprehensive and accurate obesity assessment, multiple classification systems have been proposed, notably those from the World Health Organization (WHO) and the National Health and Nutrition Examination Survey (NHANES) (13). However, inconsistencies in how these systems categorize weight status underscore the need for harmonized or comparative approaches (4,14-16). Therefore, the objective of this study is to critically evaluate the discrepancies between the WHO and NHANES classification systems in terms of how they define obesity in a Colombian cohort. We will also analyze the relationship between phase angle (PhA), BMI and other body composition variables, aiming to contribute to a more robust and precise framework for assessing obesity and body composition within this specific context.

Methods

Study design and participants

This cross-sectional study was conducted between 2017 and 2021 at a single medical center in Colombia. All patients who visited the obesity and metabolism center during this period were eligible for inclusion. A total of 3,255 patients (836 men and 2,419 women) were enrolled, while individuals with incomplete or missing data were excluded. Informed consent was obtained from all participants, and the study adhered to the institution's ethical guidelines.

Body composition assessment

Body composition was measured using a multifrequency octopolar bioelectrical impedance device (SECA® mBCA-514, Germany). Parameters assessed included fat mass (FM), skeletal muscle mass (SMM), fat-free mass (FFM), fat mass index (FMI), skeletal muscle index (SMI), phase angle (PhA), and waist-to-hip ratio (WHR). The PhA measurement was obtained at a frequency of 50 kHz. All procedures were performed by trained personnel following standardized protocols to ensure accuracy and reliability.

Statistical analysis

Descriptive statistics for continuous variables were summarized as means and standard deviations or as medians and interquartile ranges, depending on the distribution assessed via the Shapiro–Wilk test. Categorical variables were reported as frequencies and percentages. Comparisons of continuous variables between groups were conducted using either the Student's *t*-test or the Mann–Whitney *U* test, contingent upon normality assumptions. Categorical variables were compared using chi-squared tests, with a particular focus on evaluating discrepancies in obesity classifications as defined by the World Health Organization (WHO) and the National Health and Nutrition Examination Survey (NHANES). To quantify the level of agreement between WHO and NHANES categories, Cohen's kappa coefficient was calculated.

Correlations among body composition metrics were assessed through either Pearson's or Spearman's correlation coefficients, based on the distribution of each variable. The strength of the correlations was categorized based on the magnitude of the correlation coefficient (rho/ρ values) as follows: very high (ρ = 0.90–1.00), high (ρ = 0.70–0.90), moderate (ρ = 0.50–0.70), low (ρ = 0.30–0.50), and negligible (ρ = 0.00–0.30) (17). Multiple linear regression models were then employed to explore the relationship between PhA and both FMI and SMI, adjusting for BMI, age and sex. A two-tailed p-value < 0.05 was deemed statistically significant for all analyses. All statistical procedures were performed using Python 3.12 (PyCharm Professional Edition), with libraries including Pandas, NumPy, Statsmodels, scikit-learn, Seaborn, and Matplotlib.

Results

A total of 3,255 individuals were included, of whom 74.3% (n = 2,419) were women. The median age for the overall sample was 42 years

(IQR 33–53), with a median BMI of 28.0 kg/m² (IQR 24.7–32.0). Key body composition parameters included a median fat mass index (FMI) of 10.9 kg/m² (IQR 8.2–14.35) and a median phase angle (PhA) of 5.4° (IQR 5.0–5.9). Table 1 provides a comprehensive summary of these and other body composition parameters. When stratified by sex, significant differences emerged in weight (p < 0.001, BMI [p < 0.001], body fat mass [p < 0.005], and visceral adipose tissue [p < 0.001]), whereas fat-free mass, skeletal muscle mass, PhA, and waist-to-hip ratio showed no statistically significant variation (p > 0.05). Overall, although women tended to have lower median weight values than men, they displayed comparable FFM, SMM, and PhA levels. A comprehensive overview of these findings is presented in Table 2 and Figure 1.

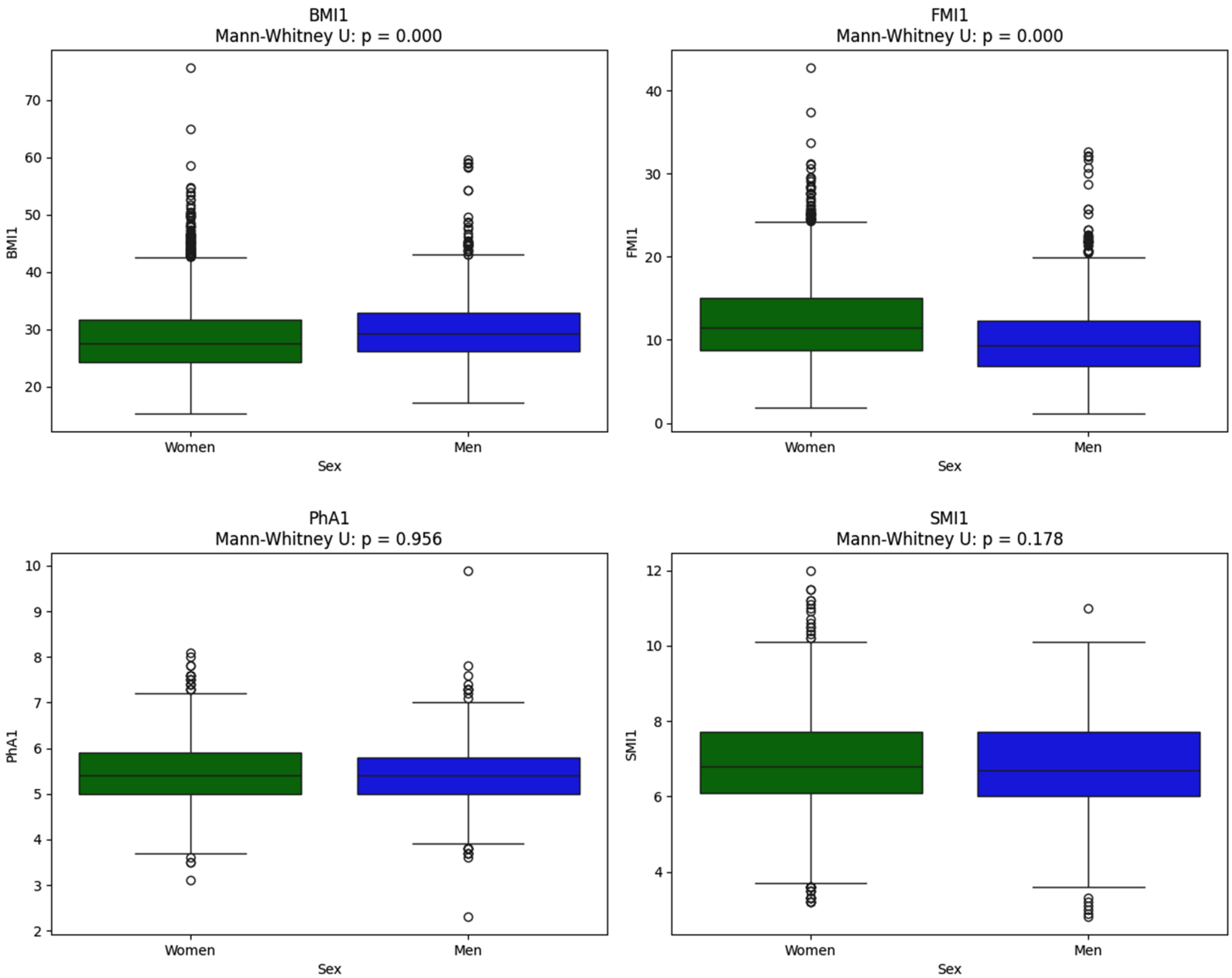

Figure 1. Comparison of BMI, FMI, PhA, and SMI by sex

Note. Box plots comparing body mass index (BMI), fat mass index (FMI), phase angle (PhA), and skeletal muscle index (SMI) between women (green) and men (blue). Statistical significance was assessed using the Mann-Whitney U test. Significant differences were observed for BMI (p = 0.000) and FMI (p = 0.000), with men showing higher median values for both. No significant differences were observed for PhA (p = 0.956) or SMI (p = 0.178), indicating similar distributions between sexes for these variables. These results highlight sex-based differences in adiposity measures but not in muscle-related or functional indicators.

Source: The authors.

Table 1. Baseline characteristics of the study population

Variable	Category	FreQUency
GENDER	F	2419 (74.3%)
	M	836 (25.7%)
OMS CLASS	Underweight	73 (2.2%)
	Normal	831 (25.5%)
	Overweight	1154 (35.5%)
	Obesity Class I	721 (22.1%)
	Obesity Class II	284 (8.7%)
	Obesity Class III	192 (5.9%)
NHANES CLASS	Severe Fat Deficit	17 (0.5%)
	Moderate Fat Deficit	11 (0.3%)
	Mild Fat Deficit	57 (1.7%)
	Normal	720 (22.1%)
	Excess Fat	1098 (33.7%)
	Obesity Class I	755 (23.1%)
	Obesity Class II	364 (11.2%)
	Obesity Class III	233 (7.2%)
		Median (IQR)
AGE		42 (33-53)
WEIGHT (kg)		75 (64.8-87.8)
BMI (kg/m^2)		28 (24.7-32)
BFM (kg)		29.5 (22.3-38)
PBF (%)		39.4 (33-46.1)
VAT (ml)		147.8 (103.4-191.6)
FMI (kg/m^2)		10.9 (8.2-14.35)
FFM1 (kg)		42.3 (37.9-49.65)

FFMI (kg/m²)		16.3 (15.1–18.2)
SMI (kg/m²)		6.7 (6.1–7.7)
PhA (°)		5.4 (5–5.9)
WHR		0.91 (0.85–0.96)

Note. All frequencies are presented as counts (percentages). Continuous variables are presented as median (interquartile range, IQR). OMS CLASS refers to the classification based on the World Health Organization criteria. NHANES CLASS refers to classifications based on the National Health and Nutrition Examination Survey thresholds. Measurements for body composition are derived from bioimpedance analysis at baseline. BMI: Body Mass Index; BFM: Body Fat Mass; PBF: Percent Body Fat; VAT: Visceral Adipose Tissue; FMI: Fat Mass Index; FFM: Fat-Free Mass; FFMI: Fat-Free Mass Index; SMI: Skeletal Muscle Index; PhA: Phase Angle; WHR: Waist-to-Hip Ratio.

Source: The authors.

Table 2. Gender-based analysis of baseline body composition and clinical metrics

Variable	Female (n:2419)	Male (n:836)	P-value
Weight	70.90 [62.50-81.30]	88.80 [78.80-101.45]	<0.01
BMI (kg/m²)	27.50 [24.30-31.60]	29.20 [26.20-32.92]	<0.01
BFM (kg)	29.90 [22.75-38.25]	28.25 [20.70-37.40]	<0.01
VAT (ml)	154.00 [111.20-194.75]	126.35 [88.30-176.03]	<0.01
FFM (kg)	42.50 [38.00-49.60]	41.90 [37.50-49.70]	0.21
SMM (kg)	23.10 [20.50-27.50]	22.80 [20.20-27.62]	0.22
PhA (°)	5.40 [5.00-5.90]	5.40 [5.00-5.80]	0.96
WHR	0.91 [0.85-0.96]	0.90 [0.85-0.95]	0.05
OMS CLASS			<0.001
	Underweight: 65 (2.7%)	Underweight: 8 (1.0%)	
	Normal: 695 (28.7%)	Normal: 136 (16.3%)	
OMS CLASS	Overweight: 841 (34.8%)	Overweight: 313 (37.4%)	
	Obesity Class I: 482 (19.9%)	Obesity Class I: 239 (28.6%)	
	Obesity Class II: 196 (8.1%)	Obesity Class II: 88 (10.5%)	
	Obesity Class III: 140 (5.8%)	Obesity Class III: 52 (6.2%)	

NHANES CLASS			<0.001
	Severe Fat Deficit: 0 (0.0%)	Severe Fat Deficit: 3 (0.4%)	
	Moderate Fat Deficit: 0 (0.0%)	Moderate Fat Deficit: 1 (0.1%)	
	Mild Fat Deficit: 0 (0.0%)	Mild Fat Deficit: 9 (1.1%)	
	Normal: 695 (28.7%)	Normal: 133 (15.9%)	
	Excess Fat: 0 (0.0%)	Excess Fat: 246 (29.4%)	
	Obesity Class I: 482 (19.9%)	Obesity Class I: 218 (26.1%)	
	Obesity Class II: 196 (8.1%)	Obesity Class II: 125 (14.9%)	
	Obesity Class III: 140 (5.8%)	Obesity Class III: 101 (12.1%)	

Note. Continuous variables are expressed as median [interquartile range], while categorical variables are presented as n (%). Statistical comparisons between genders were conducted to identify significant differences. OMS and NHANES classifications provide standardized categories for obesity and body composition assessment. BMI: Body Mass Index; BFM: Body Fat Mass; VAT: Visceral Adipose Tissue; FFM: Fat-Free Mass; SMM: Skeletal Muscle Mass; PhA: Phase Angle; WHR: Waist-to-Hip Ratio.

Source: The authors.

Chi-squared analyses revealed a significant global association between the WHO and NHANES obesity classifications (χ^2 = 8100.88, $p < 0.001$). The agreement between these two classification systems was quantified using Cohen's kappa coefficient (κ = 0.39), indicating a fair level of concordance across the entire study cohort. However, a closer look at the individual categories revealed notable differences in how patients were classified under each system. For instance, individuals classified as "Underweight" by WHO were more frequently deemed "Normal" (34.2%) or "Mild Fat Deficit" (32.9%) by NHANES, while those labeled "Normal" under WHO mostly retained the same classification (72.8%) but had a sizable proportion (22.7%) flagged as "Excess Fat."

Among individuals classified as "Overweight" by the WHO system, the majority (73.1%) shifted to "Excess Fat" under NHANES, while 18.9% were categorized as "Obesity Class I." A similar pattern was observed in higher obesity classes. WHO "Obesity Class I" correlated strongly with NHANES "Obesity Class I" (72.3%) and, to a lesser extent, "Obesity Class II" (18.0%). Likewise, WHO "Obesity Class II" largely overlapped with NHANES "Obesity Class II" (75.7%) and "Obesity Class III" (18.7%), whereas WHO "Obesity Class III" was mirrored by NHANES "Obesity Class III" in 91.7% of cases. A more comprehensive breakdown of these discrepancies is shown in Table 3, while Figure 2 offers a visual overview. Interestingly, when stratified by sex, the concordance was higher in females (κ = 0.43, moderate) compared to males (κ = 0.28, fair), which contrasts with the fair global concordance observed in the overall cohort.

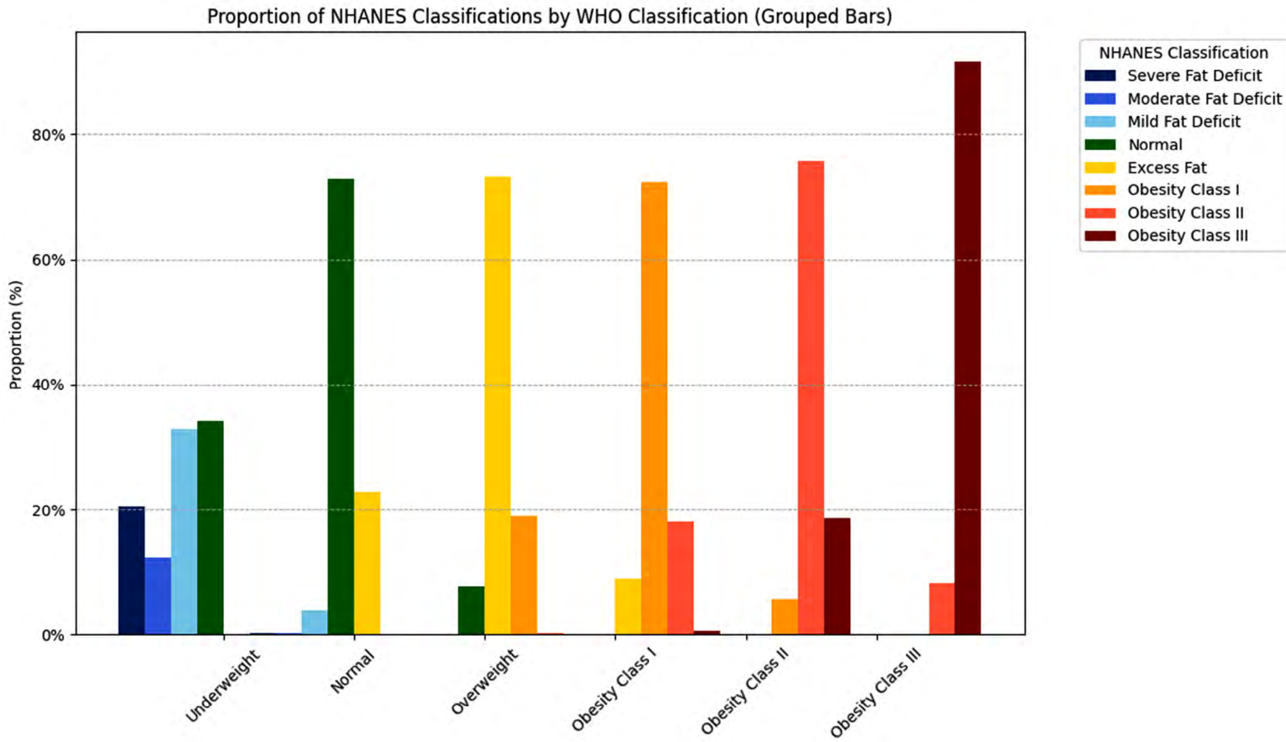

Figure 2. Proportion of NHANES classifications by WHO classification

Note. Grouped bar chart displaying the proportion of NHANES body fat classifications within each WHO BMI classification category. Each bar represents the distribution of NHANES categories (Severe Fat Deficit, Moderate Fat Deficit, Mild Fat Deficit, Normal, Excess Fat, Obesity Class I, II, and III) within a specific WHO classification (Underweight, Normal, Overweight, Obesity Class I, II, and III). The chart highlights notable discrepancies between the two systems, particularly in the extremes, where classifications diverge significantly. These results underscore the limitations of BMI-based categorizations in capturing nuanced differences in body composition.

Source: The authors.

Table 3. Distribution of NHANES classifications across WHO weight categories

WHO Class	X2	Degrees Of Freedom	P-Value	Predominant NHANES classification	Predominant percentage	Second category	Second percentage
Underweight	38.25	35	<0.001	Normal	34.20%	Mild Fat Deficit	32.90%
Normal	287.46	3	<0.001	Normal	72.80%	Excess Fat	22.70%

Overweight	393.28	4	<0.001	Excess Fat	73.10%	Obesity Class I	18.90%
Obesity Class I	255.48	3	<0.001	Obesity Class I	72.30%	Obesity Class II	18.00%
Obesity Class II	85.76	4	<0.001	Obesity Class II	75.70%	Obesity Class III	18.70%
Obesity Class Iii	17.33	2	<0.001	Obesity Class III	91.70%	Obesity Class II	8.30%

Note. This table presents the predominant and secondary NHANES classifications for each WHO weight category, along with their respective percentages. P-values indicate the statistical significance of the associations between classifications.

Source: The authors.

Global correlation analysis revealed the strongest associations ($\rho > 0.70$, $p < 0.001$) between BMI and body fat mass (BFM) (global $\rho = 0.929$), and between BFM and visceral adipose tissue (VAT) (global $\rho = 0.978$). These patterns held true across sexes, with women displaying correlations of $\rho = 0.955$ and $\rho = 0.921$, respectively, and men showing similar strengths ($\rho = 0.939$ and $\rho = 0.914$, respectively), consistently classified as very strong. In contrast, correlations involving BMI and FFM, SMM, waist-to-hip ratio (WHR), or phase angle (PhA) were negligible ($\rho < 0.30$) or nonsignificant ($p > 0.05$) in all analyses. Moderate correlations ($0.50 \leq \rho < 0.70$, $p < 0.001$) were observed between FFM or SMM and PhA, as well as with WHR in the overall sample. Notably, the correlation between FFM and WHR was classified as moderate globally ($\rho = 0.502$) but low in men ($\rho = 0.493$), reflecting subtle sex-specific differences. Collectively, these findings underscore that the most robust correlations are observed among measures of adiposity (BMI, BFM, VAT) and closely related parameters, while associations with WHR and PhA remain weaker, highlighting the multifaceted nature of body composition. Further details of these analyses are provided in Table 4.

In the multivariable linear regression model using fat mass index (FMI) as the dependent variable, overall explanatory power was modest ($R^2 = 0.950$, $F = 15291.27$, $p < 0.0001$, $RMSE = 1.0972$). Phase angle (PhA) did not reach statistical significance ($\beta = -0.0208$, $p = 0.444$), whereas BMI ($\beta = 0.7508$, $p < 0.0001$), age ($\beta = 0.0113$, 95% CI 0.008–0.014, $p < 0.0001$) and sex ($\beta = -3.3379$, 95% CI −3.425 to −3.251, $p < 0.0001$) emerged as strong predictors of FMI.

In contrast, the model for skeletal muscle index (SMI) demonstrated a considerably higher explanatory capacity ($R^2 = 0.332$, $F = 403.7$, $p < 0.0001$, $RMSE = 1.0379$). Here, PhA was highly significant ($\beta = 1.032$, 95% CI 0.982–1.083, $p < 0.0001$), whereas neither BMI ($p = 0.586$), age ($p = 0.812$) nor sex ($p = 0.095$) contributed meaningfully to the SMI variance. Taken together, these findings suggest that while BMI, age, and sex play pivotal roles in predicting adiposity (FMI), PhA exerts a negligible effect on fat mass but is a strong determinant of muscle mass (SMI). A detailed representation of these findings is provided in Figure 3.

Table 4. Correlation matrix of body composition and physiological metrics in male and female participants

Male								
	Weight	**BMI**	**BFM**	**VAT**	**FFM**	**SMM**	**PhA**	**WHR**
Weight1	0	0,904481	0,89476	0,869222	0,011328	0,01102	0,003331	0,008609
BMI (Kg/m²)		0	0,938825	0,913944	-0,00743	-0,00648	0,020184	-0,00921
BFM (Kg)			0	0,989978	-0,00684	-0,00688	0,010143	0,009366
VAT (ml)				0	-0,00348	-0,0036	0,012733	0,016299
FFM (Kg)					0	0,99886	0,572399	0,492747
SMM (Kg)						0	0,60068	0,491751
PhA (°)							0	0,155626
WHR								0
Female								
	Weight	**BMI**	**BFM**	**VAT**	**FFM**	**SMM**	**PhA**	**WHR**
Weight1	0	0,922839	0,940144	0,889279	-0,00663	-0,00695	-0,02473	0,027293
BMI (kg/m²)		0	0,955392	0,92093	-0,00942	-0,0092	-0,02151	0,024082
BFM (kg)			0	0,982315	-0,01821	-0,01813	-0,02426	0,020365
VAT (ml)				0	-0,02039	-0,02032	-0,02327	0,014251
FFM (kg)					0	0,998746	0,532742	0,50479
SMM (kg)						0	0,564704	0,505553
PhA (kg)							0	0,138872
WHR (°)								0

Note. The table presents Pearson correlation coefficients for key body composition and physiological metrics across participants of both sexes. Coefficients range from -1 to 1, indicating the strength and direction of relationships: positive (direct) or negative (inverse). Values closer to 1 or -1 reflect stronger correlations, while those near 0 suggest weaker or no association. BMI: Body Mass Index; BFM: Body Fat Mass; VAT: Visceral Adipose Tissue; FFM: Fat-Free Mass; SMM: Skeletal Muscle Mass; PhA: Phase Angle; WHR: Waist-to-Hip Ratio.

Source: The authors.

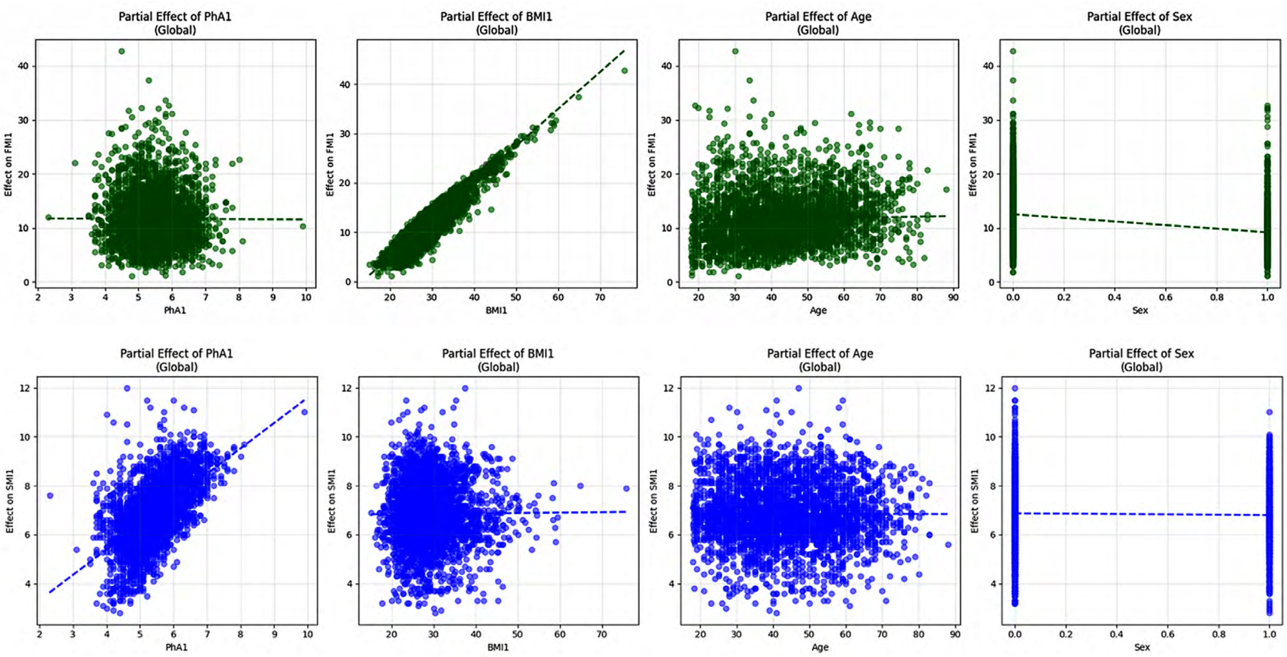

Figure 3. Partial effects of phase angle, age, and sex on fat mass index (FMI) and skeletal muscle index (SMI)

Note. Scatter plots illustrating the partial effects of phase angle (PhA), BMI, age, and sex on fat mass index (FMI) (top row) and skeletal muscle index (SMI) (bottom row) in the global analysis. The dashed lines represent the fitted trends for each predictor. The first column shows the effect of PhA, highlighting its significant influence on SMI but not FMI. The second column depicts the effect of BMI, illustrating its strong association with FMI. The third column represents the effect of age, and the fourth column captures the effect of sex, where 0 = Female and 1 = Male. These visualizations demonstrate the distinct relationships of these variables with fat and muscle compartments, supporting the importance of advanced body composition analysis in clinical assessments.

Source: The authors.

Discussion

This comprehensive analysis provides valuable insights into the relationship between traditional anthropometric measurements and advanced body composition parameters. Notably, while women exhibited lower median weight values compared to men, they demonstrated comparable levels of FFM, SMM, and PhA. These findings could challenge traditional assumptions about sex-based differences in body composition and may be particularly relevant in the Latin American context, specifically Colombia, where cultural factors such as increased physical activity levels and dietary patterns might contribute to these outcomes (13,18-20). Further research is warranted to better understand these observations, particularly in the context of cultural and regional factors that may influence body composition patterns in Latin America. Clinically, these results underscore the need for personalized treatment approaches that account for sex-specific differences in order to improve obesity management. Similar findings have been reported in previous studies, which suggest that physiological differences may significantly influence metabolic health and responses to obesity treatments (21).

The analysis of classification system concordance between WHO and NHANES revealed intriguing patterns with important clinical implications. While the overall agreement was fair, the higher concordance observed in females compared to males suggests that current classification systems may be better calibrated for women's body composition patterns (18). However, this observation could partly be explained by the larger proportion of women in our sample, which could have influenced the results. Notably, the discrepancies observed, particularly at the extremes of the distribution, underscore the limitations of BMI-based categorization systems (3,22). These findings align with growing evidence that BMI, while useful as a population-level screening tool, may not adequately capture individual variations in body composition, especially in populations with unique anthropometric characteristics (2,3,5).

The correlation analyses provided robust evidence for the relationship between different body composition parameters. The strong correlations observed between BMI and BFM ($\rho = 0.929$) validate the utility of BMI as a surrogate marker for adiposity in this population. In contrast, the moderate to weak correlations between BMI and measures of lean mass (FFM, SMM) reinforce the inherent limitations of BMI in assessing muscular components and structural body composition. These findings are particularly relevant in the clinical setting, where accurate assessment of both fat and lean mass is essential for tailoring interventions and monitoring treatment outcomes (23-25). For instance, clinicians could leverage advanced technologies that offer more comprehensive data on muscle mass and quality, facilitating the development of more precise, personalized, and effective treatment strategies.

Perhaps the most striking findings emerged from the multivariable regression analyses. The robust explanatory power of the FMI model ($R^2 = 0.950$) compared to the moderate predictive capacity of the SMI model ($R^2 = 0.332$), reveals fundamental differences in how body composition parameters interact. Specifically, BMI proved to be a strong predictor of fat mass, whereas phase angle (PhA) showed a pronounced association with muscle mass ($\beta = 1.032$, $p < 0.0001$) and minimal relevance for adiposity. Interestingly, BMI did not meaningfully correlate with muscle mass, underscoring the limitations of relying solely on BMI to evaluate muscular health.

Furthermore, age and sex emerged as significant contributors to FMI but did not meaningfully influence SMI. Taken together, these findings underscore the importance of considering BMI, age, and sex when evaluating fat mass, while highlighting PhA as a valuable tool for assessing muscle mass—a component often overlooked in traditional obesity assessments (23,26,27). Supporting the development of age-specific and sex-specific guidelines for diet and physical activity becomes essential under this paradigm. Clinically, this means that lifestyle recommendations should be tailored not just based on overall health status but also on these demographic characteristics, which could impact the efficacy of diet and exercise regimens (28).

The noted discrepancies between the WHO and NHANES systems, along with the varying correlations among different body composition metrics call for a reevaluation of current obesity classification standards. By emphasizing the significance of phase angle as a determinant of muscle mass, we underscore the necessity of incorporating functional markers in the evaluation of obesity—beyond traditional indices like BMI. Our findings highlight the need for more inclusive criteria that reflect diverse body composition profiles, especially those in underrepresented populations like Colombians. Clinically, this reevaluation could lead to more accurate risk assessment and personalized treatment pathways. By incorporating both WHO and NHANES criteria along with emerging biomarkers into a multifaceted classification approach, healthcare providers can better identify individuals at risk and tailor treatments to specific conditions like insulin resistance or hypertension (20,29,30). This is especially relevant in populations where standard anthropometric assumptions may not apply, as demonstrated by the similar muscle mass profiles observed between men and women in our study.

For example, patients with low muscle mass at high risk of insulin resistance may benefit from a dual-intervention approach: dietary modifications aimed at lowering glycemic loads and targeted pharmacotherapy to address metabolic dysfunction, complemented by progressive resistance training protocols designed to increase skeletal muscle mass, thereby optimizing metabolic flexibility and glucose utilization pathways (31-33). Meanwhile, individuals with borderline overweight or substantial visceral adiposity might achieve better outcomes through body recomposition strategies—rather than solely pursuing weight reduction—by integrating specialized physical activities, balanced macronutrient intake, and routine body composition monitoring (34–39). A multidisciplinary approach that considers muscle mass, metabolic markers, and demographic factors ensures interventions are precisely tailored to individual needs, ultimately refining obesity management and reducing long-term complications (40).

Strengths and limitations

Our study's strengths include its large sample size of 3,255 participants, which ensures robust statistical power, and the use of advanced body composition analysis to comprehensively evaluate both anthropometric and compositional parameters. Additionally, the inclusion of both sexes allowed for an exploration of sex-specific differences, enhancing the relevance of the findings. However, the study's cross-sectional nature and single-center design may limit the generalizability of results to other populations. The predominance of female participants, while reflective of typical clinical populations, may also affect the broader applicability of our findings to male populations. Future research should focus on longitudinal studies to evaluate how these relationships evolve over time and with intervention, particularly focusing on the role of PhA in predicting outcomes in weight management programs.

Conclusions

In conclusion, our study in a Colombian population reveals important sex-specific differences in body composition patterns and demonstrates that while BMI serves as an adequate predictor of adiposity, it falls short in assessing muscular mass. Traditional weight- classification systems show limitations in accurately categorizing patients, as evidenced by the distinct behavior of fat and muscle compartments in our linear regression analyses. Notably, there are significant differences between men and women that cannot be adequately captured using traditional anthropometric measurements, further highlighting the need for more precise evaluation methods. The emergence of PhA as a robust predictor of muscle mass, but not fat mass, underscores its potential utility in clinical assessment. These findings emphasize the critical importance of incorporating comprehensive body composition analysis in clinical practice, moving beyond simple weight-based metrics. Future studies should focus on integrating detailed body composition assessment into routine clinical care, particularly in diverse populations where standard anthropometric assumptions may not apply, to better inform personalized treatment strategies and improve patient outcomes.

Authors' contributions

Ricardo Rosero-Revelo (Conceptualization, Study design, Writing – original draft, Supervision, review & editing), Mateo Tamayo (Data analysis, Data interpretation, Methodology, Writing), Marcio L. Griebeler (Original draft, Supervision, review & editing).

Ethical considerations

This study was conducted in strict accordance with international ethical standards. Given its design as an observational study involving no direct contact with participants and the exclusive use of de-identified data, ethical review was not required as per institutional guidelines. Nonetheless, all procedures were carried out with a commitment to maintain data confidentiality and participant anonymity, ensuring compliance with ethical standards.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. All participants have contributed impartially, free from financial or personal influences that could undermine the integrity of this work.

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